Estimating the Causal Effect of School Size on Educational Attainment

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Abstract

This paper assesses the effect of school size on learning outcomes. Our methods include robust analyses and inverse variance matching method. We conclude that school size does not causally affect educational outcomes at early grades but do harm fourth graders' performances. We suggest keeping schools small as a strategy for improving pupils' performances at school.

Keywords: Education quality, learning outcomes, quasi-randomization

1. Introduction

Head teachers around the world and particularly in the developing world face many obstacles when attempting to manage overcrowded schools. The Education for All-Fast Track Initiative (EFA-FTI) led to an increase in schools enrollments and particularly in Africa. The number of children enrolled between 2002 and 2008 in school in African EFA-FTI countries went up 50%. In non-FTI countries the increase was 27% (EFA-FTI (2010)). It is also recognized that increases in number of students admitted at schools have not been followed by mechanisms to improve or at least maintain school quality. For instance, Senegal has made progress expanding access to education over the last eight years, but simultaneously, quality has deteriorated (DeStefano et al. (2009)). Results from national assessments (PASEC[1] (2006)) show that in Senegal, scores in Mathematics and French have declined from 1996 to 2006 for both second and fifth grades. It appears from this description that quality decreases as enrollment increases. A rising question is therefore whether deciders need to construct more schools and keep them small or, instead, whether they should allow for large schools. This paper is a tentative answer to the question. We contribute to the literature by bringing a different methodological approach to address the rarely questioned issue of school size for the developing world.

2. Literature review

The consensus on the importance of education stems from macroeconomic and social benefits related to education. Numerous studies have established a link between quality education, a, rapid economic growth and the reduction of levels of poverty and inequality (Barro and Sala-i-Martin (1995)). Education promotes high private and social returns, and is also correlated with higher individual earnings, improving health and direction of choice in reproduction (Schultz (2003)). These researches have been a useful support in convincing policy makers that universal quality education is a key ingredient in the economic and social development. As one dimension of quality, school size is a key factor of quality education and its relationships with students' learning outcomes have been extensively discussed in the educational literature (Lee and Smith (1997)) but led to no consensus.

The arguments for school consolidation are those of economies-of-scale. Conant (1959a) was the first to point to the potential benefits of large schools. The author highlighted the variety of classes that can be offered in a large school, the increased specialization of teachers afforded by better divisions of labor and the decreased average costs per student. Following the same idea, Smith and DeYoung (1988)

[1] Programme d'Analyse des Systèmes Educatifs de la CONFEMEN. CONFEMEN stands for Conférence des Ministres de l'Education des Etats et Gouvernements membres de la Francophonie.

explained that students of a small school are more likely to be demographically homogenous. School consolidation can be justified by the richness in diversity, assuming that exposure to students of different backgrounds is considered beneficial. Second, interaction with a limited number of teachers may be stuffy almost to the point of being suffocating for students. If a student has the same teacher over the course of several years, the teacher's expectation of the student may be set after the first year of such contact and obstruct or delay the progress of student's development. In a larger school, where teachers are specialized to teach only one grade level, students get a fresh start each year. Third, limited enrollment may hinder a student's social development. In a larger school, with many social groups, a student may have a better chance of finding one such group in which he feels comfortable.

Reviews and research studies in general support the conclusion that students' achievements are greater in smaller elementary (Wasley et al. (2000)). The type of relation between school size and achievements can also be related to the category of students attending the school in question, meaning that one size does not fit all. Howley (2001) in his research on the relationship between school size and student performance shows that children from disadvantaged backgrounds performed better in school when they attend small schools, while students from advantaged backgrounds tend to perform better when they are housed in large schools.

The conflicting debate on the association between school size and students' achievement could stem from the fact that smallness does not mean the same thing across studies. For example, the definition by Conant (1959b) and Conant (1967) of large school size was total school population of about 400 students. Fox (1981) considered as large schools with at least 1,000 students.

3. Data and methodology

We make use of two rounds of data collected in Senegal between November 2009 and May 2011 which includes information on head teacher, school and school environment, teacher and class, household and pupil survey (Written tests in French and Mathematics, and Oral tests. Oral tests included topics such as reading, word recognition, non-word recognition, number of sounds and letter recognition).

We dichotomized the school size by cluster analysis to form the groups that are in comparison. Thus, we form two groups that are homogenous inside but heterogeneous outside. The treatment status of schools is not stochastically determined and taking the mean difference of tests scores between groups will not yield the net impact of school size on students' attainment. To see why this is the case, we define T_i=1 if student *i* attends a large school and T_i=0 otherwise. Finally, let $Y_i(T_i)$ denote the pair of potential outcomes that student *i* attains if he or she is exposed to the treatment or the control group. We can write:

$$E(Y \mid T=1) - E(Y \mid T=0) = E(Y(1) \mid T=1) - E(Y(0) \mid T=0)$$
$$= E(Y(1) \mid T=1) - E(Y(0) \mid T=1) + E(Y(0) \mid T=1) - E(Y(0) \mid T=0)$$

E[Y(1)|T=1)]- E[Y(0)|T=1)] is the average effect of school size on tests scores of pupils attending large schools and E[Y(0)|T=1)]- E[Y(0)|T=0)] is the selection bias. This bias stems from the fact that the average situation of students attended big schools, if they were in small schools, would not be the same as the situation of the students currently going to small schools. This is the case because these two populations are not identical. A commonly admitted way to solve this selection problem would be to use an instrument variable regression. However, in this context, it seems hard to argue that any of the available background, family, class or school variables determines school size but not students' educational achievement. In the absence of an appropriate instrument, we will assume that conditional on a set of observable variables X, the treatment can be considered to be as good as randomly assigned. That is, there exists a vector X such that the selection bias is null i.e. E[Y(0)|X,T=1)]-E[Y(0)|X,T=0)]=0.

The robust analysis we propose combine propensity score (PS) weighting with regression. Doing so accomplishes some robustness to misspecification of the parametric models by both removing the correlation between the omitted covariates, and by reducing the correlation between the omitted and included variables. Robins & Rotnitzky (1995) pointed out that, if either the model for the treatment indicator given covariates, or that for the conditional mean of Y(0) and Y(1) given covariates, is correctly specified, the resulting estimator will be consistent. The reweighting approach will create a matched group with treatment and control schools that will be balanced. In the formulas we use, $1/p(X_i)$ is used to weight each observation in the treated group and $1/(1-p(X_i))$ is used as weights for control group members. The average treatment effect (ATE) is therefore given by:

$$\tau = E\left[\frac{T_i Y_i}{p(X_i)} - \frac{(1-T_i)Y_i}{1-p(X_i)}\right]$$

In the above formula, T_i is the treatment status and $p(X_i)$ in the rarely known true PS for individual *i*. However, Hirano et al. (2003) showed that estimating the propensity score leads to a more efficient estimator, asymptotically, than knowing the propensity score. As we are focusing on average treatment effect on the treated (ATT), a major modification is required in the weight scheme. In this design, the control group is reweighted to represent the average outcome that the exposed group would have exhibited in the absence of treatment.

We also use the nearest neighbor matching bias-corrected estimator introduced in Abadie & Imbens (2002) to provide an estimation of the average effect of school size on pupils attending large schools. If the matching is not exact, as it is likely to be the case in finite sample, regression analysis can be used to eliminate the remaining bias. The bias correction adjusts the differences within the matches for the differences in their covariates values and predicts the outcomes on the matched sample (only) using some regressions functions depending on the estimator of interest. Since we are interested in ATT, the bias correction is obtained by predicting the outcomes for matched controls using the regression function:

$$\mu_0(x) = E\left[Y(0) \mid X = x\right] = \hat{\alpha}_{00} + \hat{\alpha}_{01}x$$

The coefficients of the regression function are obtained as:

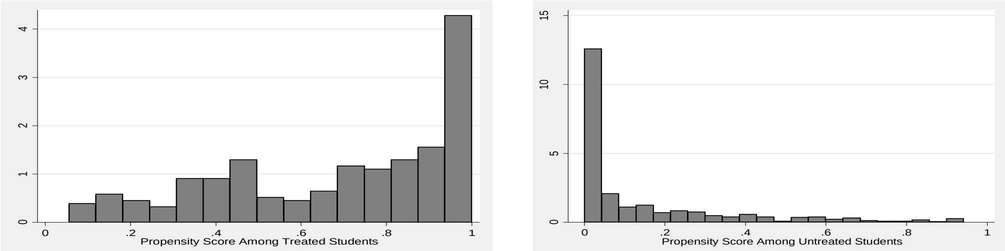
$$(\hat{\alpha}_{00}, \hat{\alpha}_{01}) = \underset{(\alpha_{00},\alpha_{01})}{\operatorname{argmin}} \sum_{\{i|T_i=0\}} K_M(i)(Y_i - \hat{\alpha}_{00} - \hat{\alpha}_{01}x_i)^2$$

$K_M(i)$ is the number of times observation i is used as control and the X_i are the covariates. The regressions are weighted by $K_M(i)$ because the weighted empirical distribution is closer to the distribution of covariates in which we are interested (Abadie et al. (2004)). While we present results from estimation with 3 neighbors, the number of neighbors is a compromise between a small variance and an unbiased estimate of the effect of school size on academic outcomes.

4. Empirical results and discussions

Our cluster analysis leads to a group of schools with average size 210 students that are compared to schools with average size 680 students for both grades. The schools of the first group, namely the small ones, have size varying from 31 to 424 students. The large schools size varies from 440 to 1400 students. In terms of schools units, we compare 133 large schools to 295 small ones at grade 2 and 140 large schools to 298 small learning communities at grade 4. The PS gives the probability that a student, given his/her covariates, attends a large school. It estimation is based on a 38 pre-treatment variables. Figure 1 provides an overview of the distributions of the estimated PS. Separate histograms are built for students attending small and large schools (treatment schools) to check whether there is sufficient overlap between the two groups. The histograms at grade 4 share the same pattern.

Figure 1 : Propensity score histograms at grade 2



We use independent balance tests to assess the severity of the selection in our sample, strategy that reveals high imbalance. Weighting by the inverse of probability of treatment leads, as one could hope, to a sample balanced for almost all variables (33 out of 38) at both grades. Remaining imbalance is control through regression. The tables showing how balance is achieved are not presented for brevity purposes. Crump et al. (2008) suggest the use of observations such that the PS lies between 0.10 and 0.90 for estimating ATE. We discard all observations with PS greater than 0.90 as we are interested in ATT, working with about 90% of our original samples. Tables 1 and 2 summarize our findings. N indicates the sample size and standard errors are in parentheses. No models are presented here, again for brevity purposes. The outcomes variables have been standardized so that the effects can be interpreted as a multiple of the outcome's standard deviation.

The raw difference is obtained through linear regression of outcomes on the treatment indicator and a constant. This suggests positive and significant (in most cases) relation of large schools size to achievements. However, these gross estimates are misleading, as the effects of confounders have not been net out. A step toward this direction involves confounding covariates in a regression. The estimated models reveal no impact for school size on learning outcomes at both grades except for longer term outcomes at grade 4. Even here, we do not offer a solution to the causal inference we intend to make. Indeed, even if the ignorability assumption holds, it is not obvious that a simple regression of outcomes on confounding covariates and a treatment indicator is the best modeling approach for estimating treatment effects. It is the case because lack of complete overlap and imbalance are two important departures for comparability. Using ordinary least squares, we could not make any causal inference in the regions of the space of pre-treatment variables where there are either no treated units or controls units. Having model the outcomes on the common support, the results do not change in terms of significance but the effects (at grade 4 in the long run) are greater in absolute value. Here again, the model estimate does assume homogeneous treatment effects to be reliable. In other words, if the treatment effects are heterogeneous, the estimated coefficients will not have a causal interpretation. To properly assess the causal effect, we model the outcomes having reweighted the data and take into account the likely heterogeneity that could characterize the treatment effects. Given this reweighted sample, attendance of any type of school is random and the coefficients possess a causal interpretation even in the presence of heterogeneity of the effects. Our models identify zero effect on learning outcomes at grade 2. Similar results are obtained in Wyse, Keesler and Schneider (2008) who concluded in no difference of achievements between students of large schools and those of smaller. However, small to middle size effects are detected at grade 4. The effects at grade 4 survive to school break as they are present in the long term outcomes, suggesting that length of exposure have mattered. Longer term outcomes of students in smaller schools are indeed greater than outcomes of other schools. Fourth graders, aged 11 on average, feel less comfortable when they attend large school settings. Given that family, the first educational institution, where mutuality and civility are taught, is the main source of students' growth and development in the early years of schooling, they are still making the transition from home to school. According to Ornstein (1990), young students need to be encouraged and nurtured.

Table 1 : Impacts of school size on learning outcomes – Grade 2

	Raw difference	OLS	OLS on common support	PSW	NNM – 3 Neighbors
French Test – 2010	0.264***	0.024	0.021	0.029	0.096
	(0.072)	(0.106)	(0.108)	(0.100)	(0.096)
	2464	711	490	640	711
Mathematics Test – 2010	0.226***	-0.058	-0.004	0.001	0.035
	(0.067)	(0.101)	(0.100)	(0.092)	(0.092)
	2464	711	490	640	711
Oral Test – 2010	0.311***	0.113	0.122	0.064	0.237**
	(0.082)	(0.109)	(0.110)	(0.105)	(0.096)
	1250	604	419	545	604
French Test – 2011	0.093	-0.048	0.004	0.057	0.020
	(0.085)	(0.136)	(0.134)	(0.125)	(0.112)
	1586	451	298	392	451
Mathematics Test – 2011	0.132	-0.088	-0.058	-0.040	-0.172
	(0.085)	(0.134)	(0.131)	(0.109)	(0.135)
	1586	451	298	392	451
Oral Test – 2011	0.219**	0.129	0.200	0.208	0.555***
	(0.100)	(0.150)	(0.158)	(0.144)	(0.133)
	776	365	245	322	365

Table 2 : Impacts of school size on learning outcomes – Grade 4

	Raw difference	OLS	OLS on common support	PSW	NNM – 3 Neighbors
French Test – 2010	0.239***	-0.104	-0.133	-0.210**	-0.134*
	(0.076)	(0.086)	(0.087)	(0.087)	(0.082)
	2396	725	495	653	725
Mathematics Test – 2010	0.269***	-0.099	-0.131	-0.169*	-0.260***
	(0.077)	(0.096)	(0.095)	(0.094)	(0.089)
	2396	725	495	653	725
Oral Test – 2010	0.213***	-0.092	-0.144	-0.233**	-0.161**
	(0.081)	(0.098)	(0.096)	(0.102)	(0.074)
	1218	641	441	586	641
French Test – 2011	0.128	-0.251**	-0.284**	-0.242*	-0.199*
	(0.087)	(0.115)	(0.122)	(0.127)	(0.116)
	1521	455	311	408	455
Mathematics Test – 2011	0.141	-0.251*	-0.320**	-0.236*	-0.144
	(0.092)	(0.128)	(0.132)	(0.129)	(0.123)
	1521	455	311	408	455
Oral Test – 2011	0.084	-0.295**	-0.312**	-0.323***	-0.329***
	(0.097)	(0.132)	(0.133)	(0.109)	(0.104)
	773	401	274	366	401

*p<0.10 **p<0.05 ***p<0.01

5. Conclusion

In this paper, we looked at the impact of school size on learning outcomes. The empirical estimation of the effects was challenging due to the endogeneity of school size. We find zero effects of school size at grade 2. At grade 4, the impacts of school size on learning outcomes are negative and significant suggesting that keeping schools small as a way of strengthening students' performances.

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